# Modeling Cognitive Functionalities of Prosthetic Arm using Conceptual Spaces

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**Abstract:** *Conceptual space framework is used for representing knowledge in cognitive systems. In this paper, we have adapted conceptual space framework for prosthetic arm considering its cognitive abilities such as receiving signals, recognizing and decoding the signal and responding with the corresponding action in order to develop a conceptual space of the prosthetic arm. Cognitive functionalities such as learning, memorizing and distinguishing configurations of prosthetic arm are achieved via its conceptual space. To our knowledge, this work is the first attempt to adapt the conceptual spaces to model cognitive functionalities of prosthetic arm. Adding to this, we have made use of different notion of concept that reflects the topological structure in concepts. To model the actions of the prosthetic arm functionalities, we have made use of force patterns to represent action. Similarly, to model the distinguishing ability, we make use of the relationship between the attributes conveyed by adapted different notion of concept.*

**Keywords:** *Cognition, Conceptual spaces, Concepts, Information granules, Prosthetic arm*

## 1. Introduction

Prosthetics is an artificial system or a device that replaces the human lost or malfunctioning body parts [1]. Prosthetics can include a wide range of devices such as pacemaker, dental implants, limbs, ear implants, etc. [2], [3]. Among these our particular interest is on upper prosthetic limbs (prosthetic arm) since upper limbs are crucial parts of human body for multiple tasks. Losing upper limb could significantly decrease an individual's function in their life. Prosthetic arm can recover certain crucial tasks of an individual in a way comparable to human arm. In general, prosthetics can be classified into three categories: non-functional prosthetics (aesthetics purpose), mechanically controlled prosthetics and body controlled prosthetics [2]. Among these types, body controlled prosthetics are complex to handle as it involves many interrelated system such as biological system – the human body, mechanical system – the prosthetic arm and the computerized system – the application software that controls the arm based on the signal from the human body. Body controlled prosthetics receives electromyography signals (EMG) from the electrodes as an input. From these raw EMG signals, information is extracted and processed further to simulate the corresponding action [4]. According to [5], these pre-processed inputs and corresponding actions can be regarded as a cognitive state. This literature also suggests that a state space model can be used for modelling the cognitive processes in the regarded cognitive states of the prosthetic arm. On the other hand, mammalian immune system is often described as cognitive system. Conceptual space framework can be used for demonstrating the cognitive functionalities of an immune system [6]. Motivated by the aforementioned literature, we aim to model the cognitive functionalities of the prosthetic arm using the conceptual space framework in this paper. For this purpose, we perform an analogical reasoning of processes in prosthetic arm using the notions of conceptual space framework. Analogy reasoning involves adaptation relational information that already exists in one domain to another application domain [7]. To our knowledge, a very few literature are available discussing the analysis of the prosthetic arm from the perspective of cognition. As mentioned earlier, we model the cognitive functionalities such as exploring the similarities and differences using the geometrical framework of conceptual spaces for the following reasons:

I. To demonstrate the applicability and utility of Gärdenfors geometric framework of conceptual spaces on prosthetic arm.
II. To achieve the cognitive functionalities of the conceptual spaces of prosthetic arm system.

The novelty of the proposed work is the application of conceptual space framework for prosthetic arm. In this work, we also adapt a different notion of concept. Generally, a concept is a pair consisting of a real world entity and its description. However, literature suggests that the conventional notion of concept does not reflect the hierarchical structure in human brain [8]. On the other hand, Gärdenfors suggest that notion of concept as 'regions' in conceptual space framework lacks precision without topological structure [9]. We address this issue by adapting three types of attribute granules namely focal, general and essential attributes. We model the distinguishing ability of the model using these three attribute since the relationship between the attributes best convey the relationship between the concepts [8]. It should be also noted that concepts of cognitive frameworks models real world instance based on their static properties (attributes). In here, we have made use of force patterns to model the functions and actions of prosthetic arm [10].

The organization of the paper is as follows. In the next section of the paper, we have presented a brief literature review on cognitive abilities of conceptual spaces. The section 3 of the paper discusses the fundamentals of the Gärdenfors geometric representation of conceptual spaces. In section 4, we have elaborated on the proposed work while the successive section discusses the experimental analysis of the proposed work. The section 6 of the paper presents discussion on our insights with regard to our proposed work followed by conclusions.

## 2. Literature Review

This section of the paper presents the review on literature concerning potential applications of conceptual spaces and granular computing approaches from the perspective of cognition. Information in a cognitive system is represented in the form of concepts. Two prominent approaches for information representation in a cognitive system are symbolic representation and associationism [11]–[14]. Gärdenfors suggests a new approach geometric structures which is neither symbolic nor associationism for describing conceptual spaces. This theory of conceptual spaces is framework for knowledge representation. Studies have reported the application of conceptual space theory to RCC8 network to understand the betweenness of the constraints [17]. Similarly, the conceptual space can be applied to immune system in order to obtain an intelligent design of immunization [6]. Adding to these, conceptual spaces can also be applied to evolution in theories such as classic mechanics, quantum mechanics and special relativity theory. Conceptual spaces provide a knowledge level called lingua franca which facilitates the process of generalization and specialization in symbolic, sub-symbolic and diagrammatic approaches [18]. Augello et.al proposed an algebra to manipulate the internal conceptual representation of the artificial agents developed using conceptual spaces [19]. In language games, mental concept and lexicon formation can be made to co-evolve using Gärdenfors framework of conceptual spaces together with Barsalou's mental simulation and ESOM neural networks [20]. Another interesting linguistic application of conceptual space is formation of link between the idea of speaker, meaning of words and usage of words [21]. Conceptual spaces were also used by researchers to define psychiatric concepts together with ontologies [22]. In the aforementioned literature, the concepts in the target domain are static. However, concepts can also be used to represents the action and their functional properties [10]. In order to add the dynamic properties of an action, force attributes essential in concept representation. Actions contain sufficient information to perceive underlying force patterns [23], [24].

The basic principle of human cognition is to recognize and distinguish objects based on its universal as well as special properties. In order to analyse the universal and special properties, arbitrary information is transformed into information granules [25]. One straight forward approach is to classify the arbitrary information into information granules such as necessary, sufficient and necessary as well as sufficient granules [26]. Similarly, concepts can also be learned using information granules [8]. Alternatively, concepts can be learned from incomplete information via granular computing techniques [27]. A concept represents relation between set of objects and its descriptions and this relation is bidirectional [28]. Studies report that three way concepts can also adapt granular computing techniques to achieve cognition [29]. It is essential for the cognitive systems to establish cognitive relation on the information learned for intelligent behaviour of the system [30], [31]. Further, a quantum theories based conceptual spaces has been proposed for the application of elderly assistance [32]. In order to distinguish a real world object, it is essential model the similarity relation by understanding their similarities and the difference [33], [34]. Literature reveals number of similarity metrics proposed using object classes, attribute class and both object and attribute classes [35]–[37]. Detailed explanation on fundamentals, theories and applications of Gärdenfors geometrical framework of conceptual spaces can be found in this literature [11]. However, we have presented brief fundamentals of geometrical framework of conceptual space in the next section of the paper.

## 3. Fundamentals of Geometrical Framework of Conceptual Spaces

According to Gärdenfors, human cognition can well be modelled using geometric structure which are neither symbolic representation and associationism [15]. Further, concepts are closely tied by the notion of similarity and the most natural approach to model similarity is through geometric structures. In the following, we present the properties and notions of the geometrical framework of conceptual spaces.

### 3.1. Properties of Conceptual Spaces

According to the geometrical framework of conceptual spaces, geometric characteristics of conceptual spaces are spatial structures with the following properties:

I. Criterion P:

A "natural concept" is a convex region of a conceptual space. The criterion P says that if an object O located between pair of pointe v1 and v2 own some relation with attributes in concept C then all the objects located between the points v1 and v2 also own the attributes possessed by the object O.

II. Criterion C:

A concept is represented as a set of convex regions in a number of domains together with information about how the regions in different domains are correlated. The criterion C says that an Object O can be described with attributes from more than one category. This gives rise to theory of prototypes. Certain objects are judged to be more representative of an attribute category than others. The most representative member of a category is called prototypical member of that category.

### 3.2. Notions of Conceptual Spaces

The geometrical framework of conceptual spaces built on geometric structures with aforementioned properties is based on the following notion:

I. Quality dimensions: Quality dimensions include properties of a real world objects. For example, temperature, brightness, colour, weight, etc., can be categorized as quality dimensions of an object.
II. Domain: A domain is set of integral and non-separable properties of an object from different quality dimensions.
III. Prototype: Among a group of objects, certain objects are more representative of the category than other. The most representative object of a category is called a prototype.
IV. Concept: A region in a conceptual space
V. Salience: Salience is the weight of the attributed under a quality dimension
VI. Similarities: Distance between the objects provides the similarity between the objects. Similar objects placed nearer in the geometrical framework of conceptual spaces.
VII. Conceptual space: A conceptual space is the collection of concepts that interrelates different quality dimensions.

Adaptation of geometrical framework of conceptual spaces implies the adaptation of properties and the notion of the framework to the target domain (prosthetic arm) [6]. In this research, we perform analogical reasoning by adapting the terminologies such as objects, attributes, quality dimensions, domains of the geometrical framework of conceptual space to prosthetic arm to achieve the cognitive functionality. In the next section, we present the details on using the conceptual space framework for modelling prosthetic arm functionalities.

## 4. Proposed Work

The proposed work models the cognitive functionalities of prosthetic arm by adapting the geometric framework. A cognitive system is usually exemplified by its cognitive functions such as receiving cues in the environment, responding to cues and capability to learn, memorize and distinguish [5]. As mentioned in previous sections, the prosthetic arm can receive sEMG signal, understand the information in the signal and respond with the corresponding action for the given signal. We aim to achieve the other functionalities such as learning, memorizing and distinguishing cues from the environment using the geometric framework of conceptual spaces as shown in Fig. 1.

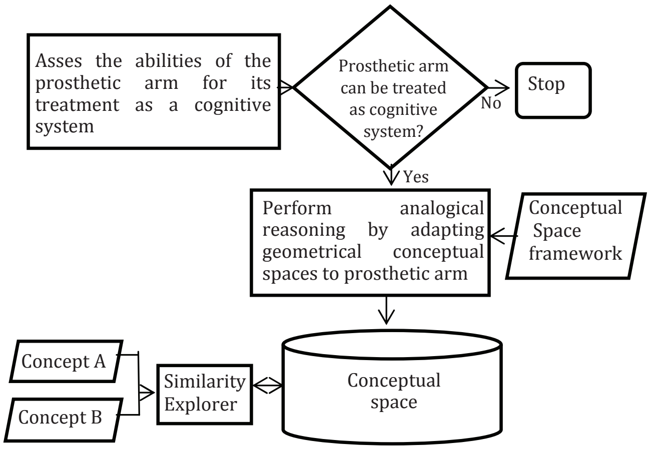


**Fig. 1.** Modelling cognitive functionalities of prosthetic arm using conceptual space framework

To adapt the geometric framework of conceptual spaces to the domain of prosthetic arm we perform analogy reasoning [7]. In here, the source domain is the geometric framework of conceptual spaces and the target domain is the prosthetic arm. The analogy between the notions of source domain and target domain is carried out as follows. We regard configurations corresponding to sEMG signals as objects, components and actions of the prosthetic arm as attributes while different categories of attributes are quality dimensions and prosthetic arm itself is the domain. The actions required to accomplish the configurations are represented in terms of their corresponding force patterns [10]. Once the objects and attributes of the conceptual space of the prosthetic arm are identified, we proceed for modelling the learning and memorizing functionalities. We model the learning process through concept generation process. A concept in the conceptual space is a pair namely configuration (object) and description of the configuration (attribute). In this work, we use three granules of attribute description for each configuration namely focal attribute, general attribute and essential attribute [8]. This proposal regards an attribute as a focal attribute if the attribute is possessed by all the configurations (cardinality of focal attribute set is greater than 2).

Similarly, an attribute is regarded an essential attribute if the attribute is possessed by only one configuration (cardinality of the essential attribute set is 1). An attribute is regarded as a general attribute if it is possessed by two or more configurations but not in all configurations (cardinality of the general attribute set is greater than 2 but less than m). For example, let us consider a set of three birds namely, crow, parrot and penguin. In this example, the focal attribute would be 'birds' since it is common to all the instances and one of the essential attribute would be 'green' since it is possessed only by 'parrot' but it is not possessed by 'crow' and 'penguin'. One of the general attribute would be 'can fly' since only 'crow' and 'parrot' can fly while 'penguin' is flightless. Consequently, each concept in the conceptual space will be of the form C:=(X, {FA, GA, EA}) where X, FA, GA, EA are the configuration, focal attribute, general attribute and essential attribute respectively. All the configurations of the prosthetic arm are learned in the form of these concepts. List of all the concepts that are learned during the concept generation process are memorized and stored in the conceptual space itself.

Another important aspect of this proposal is that it models the distinguishing ability of the conceptual space using information granules. The distinguishing ability of the model indicates the ability to understand the similarity and difference between given configurations. However, the measure of similarity is directly related to difference between the configurations, i.e. higher the differences between the configurations, the less similar they are. The proposed work models the distinguishing ability using a similarity explorer as shown in Fig. 2. The similarity explorer receives two configurations as cues to analyse similarity between them.

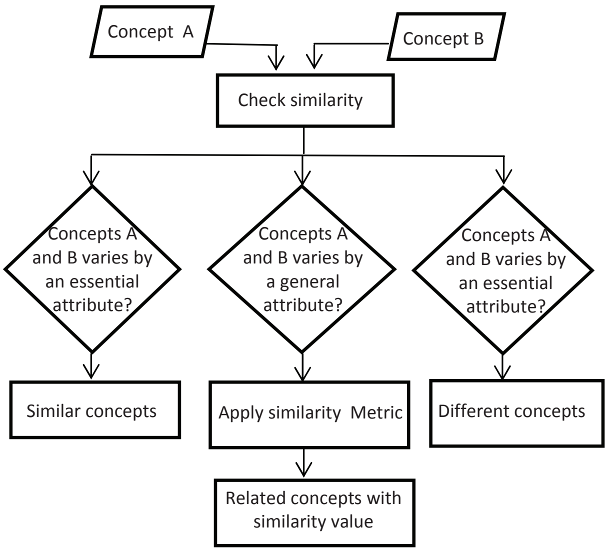


**Fig. 2.** Similarity Explorer

The similarity explorer of the proposed model classifies the given concepts as similar concepts if the concepts differ by essential attribute. Similarly, if the given concepts differ by focal attribute and general attribute, the similarity explorer classifies them as different concepts and related concepts respectively. It should be noted that the general attribute are possessed by two or more configurations (but not by all the configurations) as mentioned earlier. By this definition, a general attribute can be present in a minimum of 3 objects (say, GA1) and in a maximum of m-1 objects (say, GA2). In such case, concepts differing by GA1 are more similar than the concepts differing by GA2. To overcome this, we make use of a similarity metric shown in equation 1 as suggested by this literature [37]. Let C1:=(A1,B1) and C2:=(A2,B2) be the two concepts given as cue to the similarity explorer of the proposed model. In equation 1, the term represents attributes common in both concepts.

$$S((A_1,B_1),(A_2,B_2)) = \omega\left[\frac{(B_1\cap B_2)}{(B_1\cap B_2)+\frac{1}{2}(B_1-B_2)+\frac{1}{2}(B_2-B_1)}\right] \quad (1)$$

The terms, and represent the elements present in the attribute set B1 but not in B2 and elements present in the attribute set B2 but not in B1 and weight respectively. We set the weight since the assessment of similarity is symmetrical [36]. Using equation 1, the similarity explorer calculates the similarity measure between the given concepts. As a result, a numerical value directly proportional to the measure of similarity between the related concepts is obtained from the similarity explorer.

## 5. Experimental Analysis

Experiments are conducted to test the cognitive abilities of the proposed model. Nina pro dataset is chosen for experimental analysis as a sample of prosthetic arm functionalities [38], [39]. This dataset has EMG signals corresponding to 52 configurations performed by 67 intact subjects and 11 amputated subjects as shown in Fig. 3. The actions of Ninapro dataset is classified into four main classes namely, finger movements, hand postures, wrist movements and grasping and functional movements. The proposed model adapts the geometric framework of conceptual spaces to prosthetic arm by adapting the notions of conceptual space as shown in Table 1.

**Tab. 1.** Adapting the notion of Gärdenfors framework of conceptual space to prosthetic arm

| S. No | Notions of conceptual space | Ninapro Dataset |
|---|---|---|
| 1 | Cue(Object) | 52 configurations of Nina Pro dataset |
| 2 | Description (Attribute) | Components of prosthetic arm and force patterns of configurations |
| 3 | Quality dimensions | Four types of configuration |
| 4 | Domain | Prosthetic arm |

Here, the 52 configurations of prosthetic arm are the objects while the components and actions required to perform the configuration are the attributes of the cue. The four major classes of the configurations are quality dimensions while the prosthetic arm itself is the domain. For the purpose of convenience, we denote each configuration by combination of class id and configuration id. Class id is an alphabet (A – finger movements, B- hand postures, C- wrist movements and D- grasping and functional movements) while the configuration id is the number in

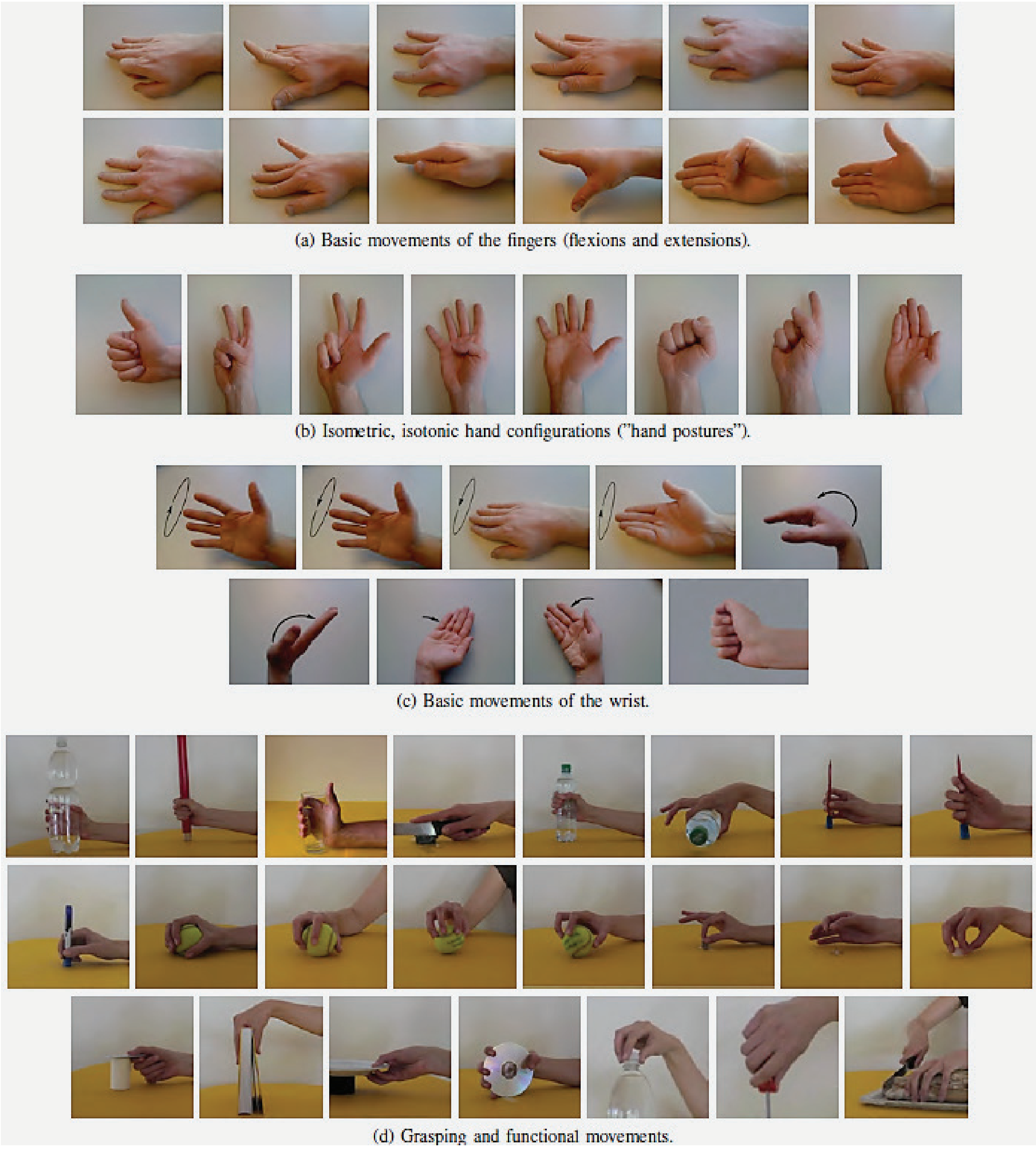


**Fig. 3.** Configurations in Ninapro dataset [39]

ascending order. There are totally 12 configurations under class A, 8 configurations under class B, 9 configurations under class C and 23 configurations under class D. For example, the first configuration of finger movement class is denoted by A1 while the last configuration under the class of grasping and functional movements is denoted by D23.

**Learning and memorizing configuration.** Prior to learning, the dataset is prepared and pre-processed. We make use the tool called Cmap (https://cmap.ihmc.us/) to create and learn the list of concepts. In order to proceed for learning, we decode the descriptions of each Nina pro dataset configuration form of propositions. Fig. 5 shows the list of the configurations learned and stored in the form of concept map by Cmap tool. We regard this concept map as conceptual space of the Nina pro dataset. In Fig. 5, configurations are represented in circle while the attributes such as focal, general and essential attributes are represented in yellow, green and grey rounded rectangle.

**Similarity exploration.** Once the concepts are learned and stored in the conceptual space, the distinguishing ability of the proposed work is tested using similarity explorer. In Table 2, we have presented a case for each type of similarity relation between two configurations.

| Prosthetic Arm | Can Do | Finger Movements |
|---|---|---|
| Grasp | Can hold | Ring |
| A11-12 | Is | Extension |
| C3-4 | Is | Suspension |
| Grasp | With | Prismatic four fingers |
| Grasp | With | Parallel extension and felxion |
| Grasp | Can hold | Fixed hook |
| B5 | Is | Abduction |
| Grasp | With | Prismatic and tip pinch |
| Grasp | With | Power, three finger and precision sphere |
| D17 | Is | Lateral |
| A5-6 | Is | Extension |
| A3-4 | Is | Flexion |
| D5 | Is | Medium wrap |
| C1-2 | Is | Wrist |
| C1-2 | Is | Suspension |
| B2 | Is | Over |
| D10-12 | Is | Power, three finger and precision sphere |
| D6 | Is | Ring |
| Grasp | Can hold | Lateral |
| Fingers | Can Be | Index Finger |
| Wrist Movements | Can do | Wrist extension |
| Fingers | Can Be | Middle Finger |
| Prosthetic Arm | Can Do | Hand Posture |
| Finger Movements | Involves | Movements |
| D21 | Is | Open a bottle |
| B3 | Is | Little Finger |
| Grasp | Can hold | Small diameter |
| Hand Posture | Involves | Oppose Base |
| Function | Can do | Cut something |
| Grasp | With | Index finger extension |
| Hand Posture | Involves | Over |
| A5-6 | Is | Ring Finger |
| C3-4 | Is | Little Finger |
| Grasping And Functional Movements | Involves | Grasp |
| D3 | Is | Fixed hook |
| A11-12 | Is | Flexion |
| A9-10 | Is | Adduction |
| Function | Can do | Writing tripod |
| D1-2 | Is | Small diameter |

| Prosthetic Arm | Can Do | Finger Movements |
|---|---|---|
| A7-8 | Is | Extension |
| Movements | Can Be | Extension |
| A5-6 | Is | Flexion |
| A3-4 | Is | Middle Finger |
| Grasp | Can hold | Stick |
| Hand Posture | Involves | Flexed Together |
| Hand Posture | Involves | Close |
| C9 | Is | Wrist extension |
| D18-19 | Is | Parallel extension and felxion |
| D4 | Is | Grasp |
| Wrist Movements | Can do | Pronation |
| B8 | Is | Close |
| D20 | Is | Power disk |
| D14-15 | Is | Prismatic and tip pinch |
| Function | Can do | Turn a screw |
| Grasp | Can hold | Tripod |
| B6 | Is | Flexed Together |
| B7 | Is | Index Finger |
| Grasp | Can hold | Large diameter |
| | D8 | Is Stick |
| C3-4 | Is | Pronation |
| C9 | Is | Close |
| A11-12 | Is | Thumb Finger |
| Prosthetic Arm | Can Do | Grasping And Functional Movements |
| A1-2 | Is | Index Finger |
| Function | Can do | Open a bottle |
| D23 | Is | Cut something |
| A9-10 | Is | Thumb Finger |
| Prosthetic Arm | Can Do | Wrist Movements |
| A1-2 | Is | Flexion |
| D16 | Is | Quadpad |
| B2 | Is | Little Finger |
| Wrist Movements | Can do | Deviations |
| Movements | Can Be | Abduction |
| B5 | Is | Fingers |
| D4 | Is | Index Finger |
| A3-4 | Is | Extension |
| Movements | Can Be | Adduction |
| A1-2 | Is | Extension |
| B6 | Is | Fingers |

| Prosthetic Arm | Can Do | Finger Movements |
|---|---|---|
| A9-10 | Is | Abduction |
| Wrist Movements | Can do | Suspension |
| Grasping And Functional Movements | Involves | Function |
| D7 | Is | Prismatic four fingers |
| Fingers | Can Be | Ring Finger |
| B2 | Is | Ring Finger |
| A7-8 | Is | Flexion |
| Grasp | Can hold | Quadpad |
| C5-6 | Is | Wrist flexion |
| D4 | Is | Extension |
| Wrist Movements | Can do | Wrist flexion |
| A7-8 | Is | Little Finger |
| Grasp | Can hold | Medium wrap |
| Finger Movements | Needs | Fingers |
| D22 | Is | Turn a screw |
| B3 | Is | Ring Finger |
| Hand Posture | Involves | Point |
| B7 | Is | Point |
| C5-6 | Is | Wrist extension |
| B4 | Is | Little Finger |
| B4 | Is | Thumb Finger |
| Fingers | Can Be | Thumb Finger |
| B2 | Is | Thumb Finger |
| Hand Posture | Involves | Up |
| C3-4 | Is | Wrist |
| B1 | Is | Thumb Finger |
| Movements | Can Be | Flexion |
| B2 | Is | Flexion |
| B8 | Is | Fingers |
| B3 | Is | Flexion |
| D1-2 | Is | Large diameter |
| D9 | Is | Writing tripod |
| Wrist Movements | Needs | Wrist |
| B4 | Is | Oppose Base |
| Grasp | Can hold | Power disk |
| B1 | Is | Up |
| Fingers | Can Be | Little Finger |
| C1-2 | Is | Pronation |
| C7-8 | Is | Deviations |
| D13 | Is | Tripod |

**Fig. 4.** Decoding configurations into proposition based on their attributes

**Tab. 2.** Case study on distinguishing configurations on Nina pro dataset

| Case | Case 1 | Case 2 | Case 3 |
|---|---|---|---|
| Configuration A | A1: Index finger flexion | A1: Index finger flexion | A1: Index finger flexion |
| Configuration B | A3: Middle finger flexion | C7: Pointing index finger | G1: Walking |
| Similarity Type | Similar concepts | Related concepts | Different concepts |
| Reason | Differed by essential attribute 'index finger' and 'middle finger' | Differed by general attribute 'movement' and 'hand postures' as well as differed by essential attribute 'flexion' and 'point' | Differed by focal, general and essential attribute |
| Similarity Measure | 0.25 | 0.17 | 0 |

*Case 1* – Similar concepts: Let the two configuration for which we wish to explore similarity be 'index finger flexion' (A1) and 'middle finger flexion' (A3) as shown in Table 2. The similarity explorer of the proposed model distinguishes A1 and A3 as similar concept. The concepts A1 and A3 are similar by the focal and the general attribute but different by essential attributes 'Index finger' and 'Middle finger' and hence classified as similar concepts by the similarity explorer of the proposed model.

*Case 2* – Related concepts: Let the two configuration for which we wish to explore similarity be 'index finger flexion' (A1) and 'pointing index finger' (C7) as shown in Table 2. The similarity explorer of the proposed model classifies the configurations as related concepts since they have same focal attribute but different general and essential attribute as 'flexion' belong to 'movements' and 'point' belong to 'hand postures' as shown in Fig. 5.

The concepts are classified into related concepts since they differ by general attribute 'flexion' and 'hand posture'. The numerical measure of similarity between these two configurations is presented in later parts of this section.

*Case 3* – Different concepts: Let the two configuration for which we wish to explore similarity be 'index finger flexion' (A1) and 'walking' (imaginary configuration under a different conceptual space say, 'prosthetic leg'). The similarity explorer has classified these two concepts as different concepts. This is because that the focal attribute is prosthetic arm and it is the root or base of the conceptual space as shown in Fig. 5. If there exist, another focal attribute, it would lead to the formation of different conceptual space. In

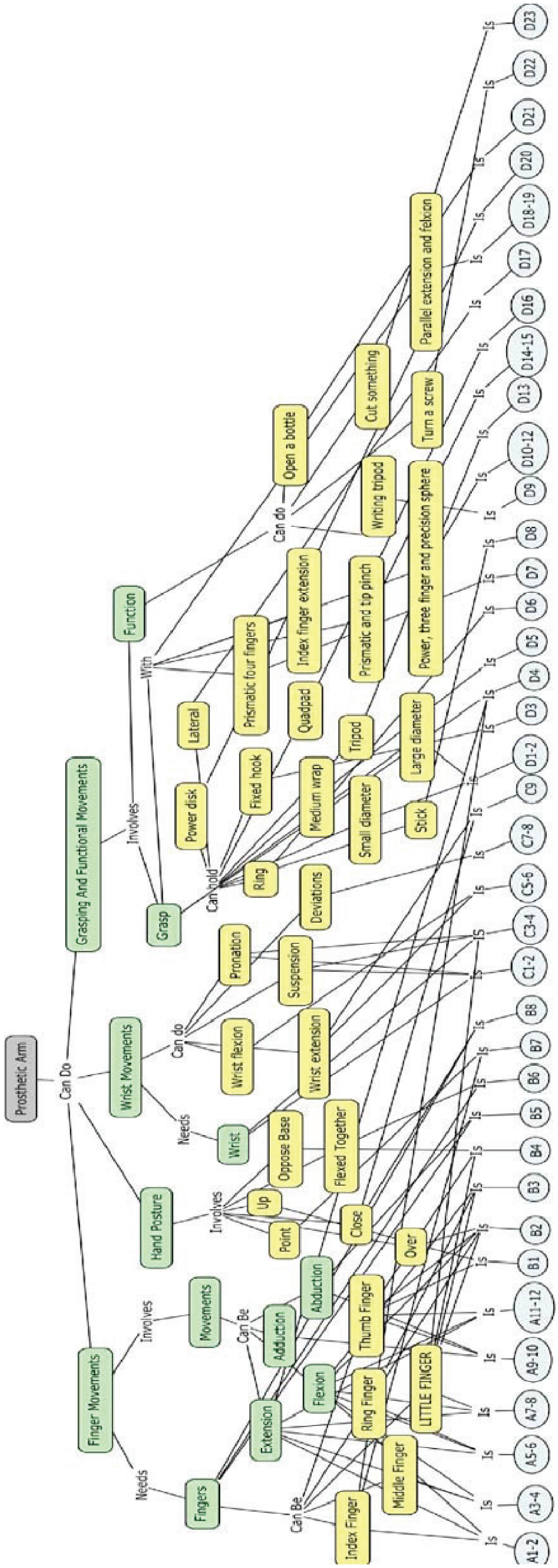


**Fig. 5.** Conceptual space of Nina pro dataset

the following, we evaluate the distinguishing ability of the model for each aforementioned case using the similarity metric shown in equation 1. We set since the assessment of similarity is symmetrical [36].

*Case 1-* Similar concepts: In order to calculate the similarity for this case, let concept A:= (X1,Y1)= ({A1},{(prosthetic arm), (finger , movements),(index finger, flexion)}) and concept B:=(X2,Y2)=({A3},{Middle finger, flexion}). Considering A and B, we obtain|Y1 Y2|=1, |Y1-Y2|= 1and |Y2-Y1|=1

$$S((X1,Y1),(X2,Y2))=\frac{1}{2}\left(\frac{1}{1+\frac{1}{2}+\frac{1}{2}}\right)=0.25$$

*Case 2:* Related concepts: In order to calculate similarity for this case, let Concept A:= (X1,Y1)= ({A1},{(prosthetic arm), (finger , movements),(index finger, flexion}) concept B:=(X2,Y2)=({C7},{(prosthetic arm), (finger , hand posture),(Index finger, point)}). considering A and B, we obtain|Y1 Y2|=1, |Y1-Y2|= 2 and |Y2-Y1|=2

$$S((X1,Y1),(X2,Y2))=\frac{1}{2}\left(\frac{1}{1+\frac{1}{2}\times 2+\frac{1}{2}\times 2}\right)=0.17$$

*Case 3:* Different concepts: For different concepts, the similarity measure will be close to zero. Consider the numerator of the metric which is union of two concepts of interest. Since the focal attributes are different, the concepts do not possess common attributes leading to the numerator of the metric 0. This will further lead to the similarity value 0. It can be inferred from the evaluation that concepts with high similarity yield higher numerical values in similarity analysis as shown in last column 2. According to Gärdenfors, the notion of concept is imprecise in the geometrical framework of conceptual spaces without topological structure [38]. In his theory, a concept is a region formed by quality dimensions where each quality dimension represents the features of the objects. However, human cognition shows higher correlation to both featural and structural information [36]. In this paper, the structural information of a concept is represented using information granules such as focal, general and essential attributes in addition to actual attribute (feature) information as shown in Fig. 5. The introduction of attributes classes preserves the property of the conceptual space that similar concepts are held nearer than different concepts. With this improved notion of concepts, we have modelled the cognitive abilities of prosthetic arm.

## 6. Conclusion

The main objective of the proposed work is to model the cognitive functionalities of prosthetic arm using conceptual space framework. For this purpose, we have regarded prosthetic arm as a cognitive system considering its abilities such as receiving, recognizing and responding cues from the environment. The notions of conceptual space framework are adapted to prosthetic arm domain. We have also adapted a different notion of concept for handling dynamic actions and preserving the relationship between the attributes during concept learning. As a result, cognitive functionalities of the prosthetic arm such as learning, memorizing and distinguishing between the configurations are modelled. In this paper, we have used the set of configurations and its descriptions for our illustrative experiments. However, conducting real-time experiments based on actual sEMG signal corresponding to Ninapro data set exercises would be one of the potential future works of this research.

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## COMPLIANCE WITH ETHICAL STANDARDS

This article does not contain any studies with human participants or animals performed by any of the authors.

## CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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## REFERENCES

[1] M. C. Amoretti, M. Frixione, A. Lieto, and G. Adamo. "Ontologies, Mental Disorders and Prototypes". In: D. Berkich and M. V. d'Alfonso, eds., *On the Cognitive, Ethical, and Scientific Dimensions of Artificial Intelligence: Themes from IACAP 2016*, Philosophical Studies Series, 189–204. Springer International Publishing, Cham, 2019
DOI: 10.1007/978-3-030-01800-9_10.

[2] R. A. Andersen, B. Pesaran, P. Mitra, D. Meeker, K. V. Shenoy, S. Cao, and J. W. Burdick, *"Cognitive state machine for prosthetic systems"*, patent no. 6952687, 2005.

[3] M. Asano, I. Basieva, A. Khrennikov, M. Ohya, Y. Tanaka, and I. Yamato, "Quantum Information Biology: From Information Interpretation of Quantum Mechanics to Applications in Molecular Biology and Cognitive Psychology", *Foundations of Physics*, vol. 45, no. 10, 2015, 1362–1378
DOI: 10.1007/s10701-015-9929-y.

[4] M. Atzori, A. Gijsberts, S. Heynen, A.-G. M. Hager, O. Deriaz, P. van der Smagt, C. Castellini, B. Caputo, and H. Müller, "Building the Ninapro database: A resource for the biorobotics community". In: *2012 4th IEEE RAS EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, 2012, 1258–1265
DOI: 10.1109/BioRob.2012.6290287.

[5] M. Atzori and H. Müller, "The Ninapro database: A resource for sEMG naturally controlled robotic hand prosthetics". In: *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2015, 7151–7154
DOI: 10.1109/EMBC.2015.7320041.

[6] A. Augello, S. Gaglio, G. Oliveri, and G. Pilato, "An algebra for the manipulation of conceptual spaces in cognitive agents", *Biologically Inspired Cognitive Architectures*, vol. 6, 2013, 23–29
DOI: 10.1016/j.bica.2013.07.004.

[7] R. Belohlavek, "Introduction to Formal Concept Analysis", 2008.

[8] T. R. Besold and K.-U. Kühnberger, "Towards integrated neural-symbolic systems for human-level AI: Two research programs helping to bridge the gaps", *Biologically Inspired Cognitive Architectures*, vol. 14, 2015, 97–110
DOI: 10.1016/j.bica.2015.09.003.

[9] H. Burnett and O. Bonami, "A Conceptual Spaces Model of Socially Motivated Language Change", *Proceedings of the Society for Computation in Linguistics*, vol. 2, no. 1, 2019, 135–145
DOI: 10.7275/5vmp-cs05.

[10] S. M. de Paula and R. R. Gudwin, "Evolving conceptual spaces for symbol grounding in language games", *Biologically Inspired Cognitive Architectures*, vol. 14, 2015, 73–85
DOI: 10.1016/j.bica.2015.09.006.

[11] B. Fan, E. C. C. Tsang, W. Xu, D. Chen, and W. Li, "Attribute-oriented cognitive concept learning strategy: a multi-level method", *International Journal of Machine Learning and Cybernetics*, vol. 10, no. 9, 2019, 2421–2437
DOI: 10.1007/s13042-018-0879-5.

[12] W. Fierz, "Conceptual Spaces of the Immune System", *Frontiers in Immunology*, vol. 7, 2016
DOI: 10.3389/fimmu.2016.00551.

[13] P. Gärdenfors, "Reasoning in conceptual spaces", *Reasoning: Studies of Human Inference and Its Foundations*, 2008, 302–320.

[14] P. Gärdenfors, *Conceptual spaces: the geometry of thought*, MIT Press: Cambridge, Mass, 2000.

[15] P. Gärdenfors. "Representing Actions and functional properties in conceptual spaces". In: *Body,language and mind*, vol. 1, 167–196, 2007.

[16] S. Schockaert and S. Li, "Reasoning about Betweenness and RCC8 Constraints in Qualitative Conceptual Spaces", 2018, 1963–1969.

[17] E. E. Hayslett-Ubell, "Upper limb prosthetics", *Wheaton Journal of Neuroscience Senior Seminar Research*, vol. 1, 2016.

[18] H. Hoffmann, J. Choe, and C. M. Thibeault. "Device and method to automatically tune the nerve stimulation pattern of a sensory-feedback capable prosthesis", patent no. 10166394, 2019.

[19] C. Huang, J. Li, C. Mei, and W.-Z. Wu, "Three-way concept learning based on cognitive operators: An information fusion viewpoint", *International Journal of Approximate Reasoning*, vol. 83, 2017, 218–242
DOI: 10.1016/j.ijar.2017.01.009.

[20] C. Li, J. Li, and M. He, "Concept lattice compression in incomplete contexts based on K-medoids clustering", *International Journal of Machine Learning and Cybernetics*, vol. 7, no. 4, 2016, 539–552
DOI: 10.1007/s13042-014-0288-3.

[21] J. Li, C. Huang, J. Qi, Y. Qian, and W. Liu, "Three--way cognitive concept learning via multi-granularity", *Information Sciences*, vol. 378, 2017, 244–263
DOI: 10.1016/j.ins.2016.04.051.

[22] A. Lieto, A. Chella, and M. Frixione, "Conceptual Spaces for Cognitive Architectures: A lingua franca for different levels of representation", *Biologically Inspired Cognitive Architectures*, vol. 19, 2017, 1–9
DOI: 10.1016/j.bica.2016.10.005.

[23] B. Markman and D. Gentner, "Commonalities and differences in similarity comparisons", *Memory & Cognition*, vol. 24, no. 2, 1996, 235–249
DOI: 10.3758/BF03200884.

[24] G. Masterton, F. Zenker, and P. Gärdenfors, "Using conceptual spaces to exhibit conceptual continuity through scientific theory change", *European Journal for Philosophy of Science*, vol. 7, no. 1, 2017, 127–150, 10.1007/s13194-016-0149-x.

[25] N. Masuyama, C. K. Loo, and N. Kubota, "Quantum-Inspired Bidirectional Associative Memory for Human–Robot Communication", *International Journal of Humanoid Robotics*, vol. 11, no. 02, 2014, 1450006
DOI: 10.1142/S0219843614500066.

[26] J. Niu, C. Huang, J. Li, and M. Fan, "Parallel computing techniques for concept-cognitive learning based on granular computing", *International Journal of Machine Learning and Cybernetics*, vol. 9, no. 11, 2018, 1785–1805
DOI: 10.1007/s13042-018-0783-z.

[27] Norton, K., "A brief History of Prosthetics", *InMotion*, vol. 17, no. 7, 2007, 1–3
DOI: 10.1161/01.CIR.0000035036.22612.2B.

[28] Ch. Aswani Kumar, M. S. Ishwarya, and C. K. Loo, "Formal concept analysis approach to cognitive functionalities of bidirectional associative memory", *Biologically Inspired Cognitive Architectures*, vol. 12, 2015, 20–33
DOI: 10.1016/j.bica.2015.04.003.

[29] R. Shivhare, A. K. Cherukuri, and J. Li, "Establishment of Cognitive Relations Based on Cognitive Informatics", *Cognitive Computation*, vol. 9, no. 5, 2017, 721–729
DOI: 10.1007/s12559-017-9498-9.

[30] A. J. Thurston, "Paré and Prosthetics: The Early History of Artificial Limbs", *ANZ Journal of Surgery*, vol. 77, no. 12, 2007, 1114–1119
DOI: 10.1111/j.1445-2197.2007.04330.x.

[31] R. Shivhare and A. K. Cherukuri, "Three-way conceptual approach for cognitive memory functionalities", *International Journal of Machine Learning and Cybernetics*, vol. 8, no. 1, 2017, 21–34
DOI: 10.1007/s13042-016-0593-0.

[32] M. S. Ishwarya and C. Aswani Kumar, "Quantum Inspired High Dimensional Conceptual Space as KID Model for Elderly Assistance". In: A. Abraham, A. K. Cherukuri, P. Melin, and N. Gandhi, eds., *Intelligent Systems Design and Applications*, 2020, 98–107
DOI: 10.1007/978-3-030-16660-1_10.

[33] A. Tversky, "Features of similarity", *Psychological Review*, vol. 84, no. 4, 1977, 327–352
DOI: 10.1037/0033-295X.84.4.327.

[34] S. Vosniadou and A. Ortony, eds., *Similarity and Analogical Reasoning*, Cambridge University Press: Cambridge, 1989.

[35] H. Wang and C. Schmid, "Action Recognition with Improved Trajectories". In: *2013 IEEE International Conference on Computer Vision*, 2013, 3551–3558
DOI: 10.1109/ICCV.2013.441.

[36] L. Wang and X. Liu, "A new model of evaluating concept similarity", *Knowledge-Based Systems*, vol. 21, no. 8, 2008, 842–846
DOI: 10.1016/j.knosys.2008.03.042.

[37] K. X. S. de Souza and J. Davis, "Aligning Ontologies and Evaluating Concept Similarities". In: R. Meersman and Z. Tari, eds., *On the Move to Meaningful Internet Systems 2004: CoopIS, DOA, and ODBASE*, Berlin, Heidelberg, 2004, 1012–1029
DOI: 10.1007/978-3-540-30469-2_12.

[38] W. Xu, J. Pang, and S. Luo, "A novel cognitive system model and approach to transformation of information granules", *International Journal of Approximate Reasoning*, vol. 55, no. 3, 2014, 853–866
DOI: 10.1016/j.ijar.2013.10.002.

[39] F. Zenker and P. Gärdenfors, eds., *Applications of Conceptual Spaces: The Case for Geometric Knowledge Representation*, Synthese Library, Springer International Publishing, 2015
DOI: 10.1007/978-3-319-15021-5.

[40] Y. Zhao, J. Li, W. Liu, and W. Xu, "Cognitive concept learning from incomplete information", *International Journal of Machine Learning and Cybernetics*, vol. 8, no. 1, 2017, 159–170
DOI: 10.1007/s13042-016-0553-8.